A Framework for Model-Based Diagnostics and Prognostics of Switched-Mode Power Supplies

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ABSTRACT

With electrical power supplies playing an important role in the operation of aircraft systems and sub-systems, flight and ground crews need health state awareness and prediction tools that accurately diagnose faults, predict failures, and project remaining life of these onboard power supplies. Among onboard power supplies, switch-mode power supplies are commonly used where their weight, size, and efficiency make them preferable to conventional transformer-based power supplies. In this paper, we present a framework of diagnostics and prognostics methodology based on an equivalent circuit system simulation model developed from a commercially available switch-mode power supply, and empirical component degradation models. In industrial applications, case-specified modifications can be made according to specific experimental or service conditions of different commercial products. First, the developed simulation model is validated through experimental testing. Then, a series of data are collected from simulation to build the baseline and fault databases under a fixed load profile. Next, promising features are extracted from sensed parameters, and further data analysis are conducted to estimate the current health condition and to predict the remaining useful life of the target system. Some highlights of the work are included but not only limited to the following aspects: first, the methodology is based on electronic system simulation instead of traditional accelerated testing by employing a high-fidelity system simulation model and empirical critical component degradation models; second, efforts are made in this preliminary work to adapt proven prognostics and health management techniques from machinery to electronic health management, with the goal of expanding the realm of electronic diagnostics and prognostics.

1. INTRODUCTION

Electronic systems such as electronic controls, onboard computers, communications, navigation and radar perform many critical functions in onboard military and commercial aircrafts. All of these systems depend on electrical power supplies for direct current power at a constant voltage to drive solid-state electronics. With these power supplies playing an important role in the operation of aircraft systems and sub-systems, flight and ground crews need health state awareness and prediction tools that diagnose faults accurately, predict failures, and project remaining useful life (RUL) of these components. Among various electrical power supplies, switch-mode power supplies (SMPS's) are commonly used in onboard aircrafts where their weight, size, and efficiency make them preferable to conventional transformer-based power supplies.

Traditional reliability practices applied in electronics are limited to reliability analysis based on historic reliability statistics and ageing models/factors of population-specific components from commonly accepted resources. Few efforts target at developing high fidelity models for specific electronic systems. On the other hand, many current prognostic and health management (PHM) practices rely on extensive highly accelerated life testing (HALT) to obtain degradation/failure data or models, which may substantially increase product life cycle costing (Brown, D. W., Kalgren, P. W., & Roemer, M. J., 2007). To address the need of developing higher fidelity models and reducing the life cycle costing, this paper proposes the use of a model-based diagnostics and prognostics approach for specific electronic systems, integrating reliability statistics, domain expertise, with experimental testing verification. More specifically, in this paper, the efforts are made to develop processes that adapt proven PHM concepts from machinery health management to electronic systems with the utilization of an integrated simulation model combining two empirical models in the application of SMPS: a circuit-based SMPS simulation model and the components' degradation models

developed based on domain expertise and validated via experimental testing.

A schematic diagram of the proposed model-based SMPS diagnostics and prognostics methodology is as shown in Figure 1. First, a high-fidelity SMPS system simulation model is established and validated via actual system testing under a fixed load profile. Single critical component is selected with the consideration of both the reliability statistics and the specific application. Then, in the fault diagnostics module, simulated data are generated to build baseline and fault databases under the same load profile. Probability of detection (POD) is selected and calculated over time for the purpose of fault detection and the trigger of failure prognosis. In the failure prognostics module, system degradation model is developed and then a model-based particle filter routine is adopted to estimate the model parameters and finally, predict RULs. Note that, all models, experimental results and analysis discussed in this paper pertain to a commercial-available SMPS as shown in Figure 2. The target SMPS system is a constant current source with the output current of 700mA ±15mA.

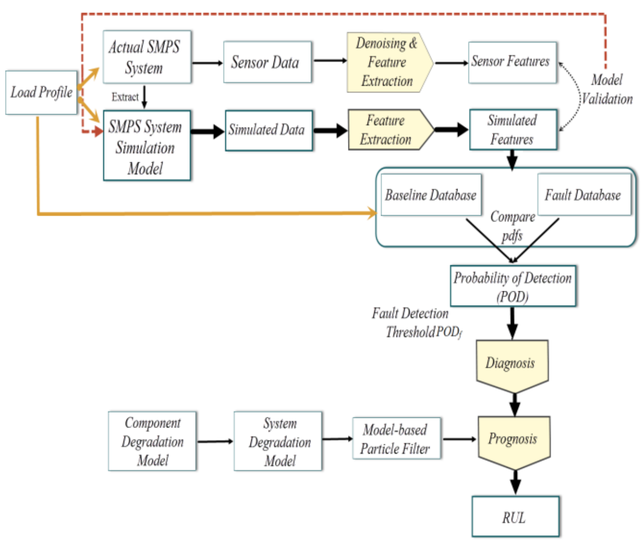


Figure 1. Systematic diagram of the proposed methodology.

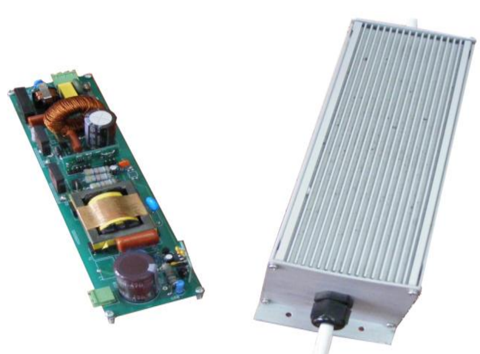


Figure 2. The SMPS commercial product.

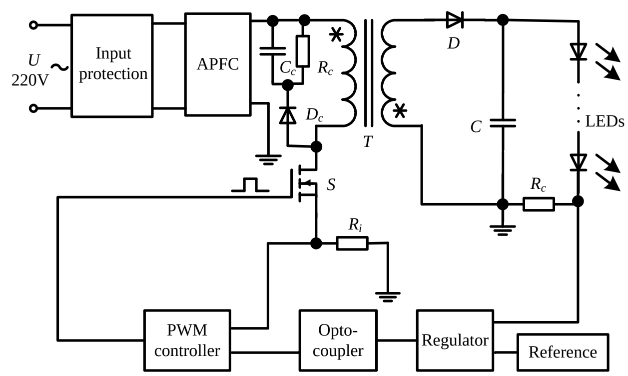
2. MODELING METHODOLOGY

In this section, the above-mentioned two types of empirical models are introduced: the circuit-based SMPS system simulation model and the critical components' degradation models, from which an integrated simulation model is generated to serve in the framework of diagnostics and prognostics to be introduced in Section 3.

2.1 SMPS System Modeling

2.1.1 Model Development

A circuit-based simulation model for the target SMPS system was developed using software PSpice. OrCAD PSpice is a *Simulation Program with Integrated Circuit Emphasis* (SPICE) analog circuit and digital logic simulation and analysis program, which is widely used in academia and industry. First, equivalent circuit models were built for individual components, for example, transformers. Then, all component models were integrated to build the SMPS system circuit model as shown in Figure 3. The whole SMPS consists of the input protecting circuit, Active Power Factor Corrector (APFC), opto-isolator, comparing regulator and other parts. The loads are 44 LEDs in serial connection, as shown in Figure 3.



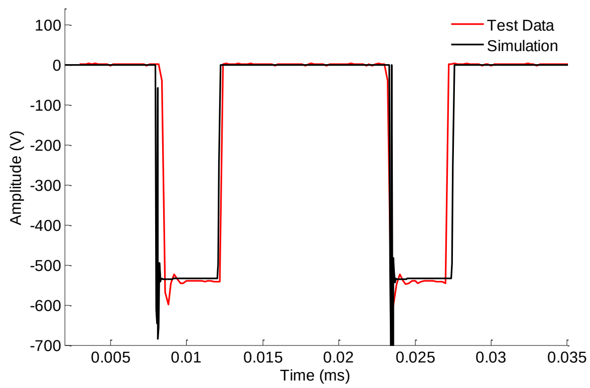
C in this circuit is the aluminum electrolytic capacitor that will age.

Figure 3. SMPS model schematic diagram.

2.1.2 Model Validation

Model validation is crucial to the high-fidelity simulation model establishment. To validate the established model, critical model parameters are usually compared to the corresponding experimental outputs from selected testing points. In this case, several comparison parameters were selected such as MOSFET drive signals (i.e., V_{gs}, V_{ds}) and diode D voltage. The MOSFET drive signal waveforms from the model and the experiment are as shown in Figure 4 as an example. As indicated in Figure 4, the model performances generally match with the experimental results, and the simulation model is validated. Note that in Figure 4, according to the authors' domain experience, high-frequency oscillation observed at the simulated waveform

changing edges could be attributed to the simulation algorithm design, and the small discrepancy between simulation and testing values could be due to the testing temperature variation and/or the actual system's Pulse-Width Modulation (PWM) chip output voltage variation.



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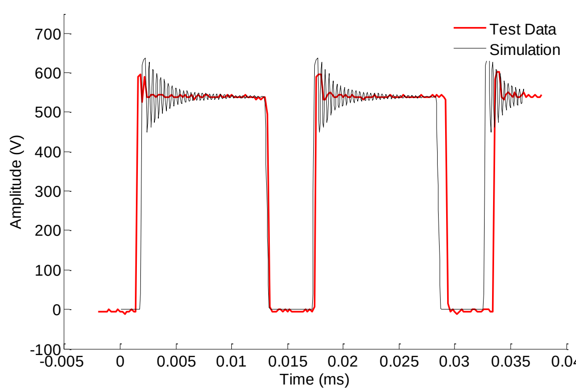


(b)

Figure 4. Simulation and experimental test waveforms of MOSFET drive signals: (a) V_{gs}, (b)V_{ds}.

2.2 SMPS Degradation Modeling

It has been established in several works (Zhang, Kang, Luo and Pecht, 2009; Goodman, Hofmeister, and Judkins, 2007) that component degradation, especially the critical components' degradation, is the prime contributor to SMPS system degradation and eventually functional failure. Thus, it is essential to identify the critical components and study their degradation progression trends. Here our interest is to study the target SMPS system's soft failure induced by system's functional degradation under a fixed load profile, and our hypothesis is that the SMPS system's degradation is only caused by the single critical component's degradation. Thus, the system assumes the same degradation model as the critical component.

2.2.1 Critical Component Identification

Previous reliability studies of typical SMPS components have shown that the majority of failures may be attributed to a list of critical components such as *metal-oxide semiconductor field-effect transistors* (MOSFETs), aluminum electrolytic capacitors and silicon power rectifier diodes (Li, D., & Li, X., 2012). The failures of those components correspond to approximately 80% of the total failures. In this work, in addition to component reliability studies, a failure mode and effects analysis (FMECA) was also conducted to generate a list of critical components for this specific commercial SMPS. In this paper, for the purpose of illustration of methodology, aluminum electrolytic capacitor and feedback resistor are selected for single critical component degradation study.

2.2.2 Critical Component Degradation Modeling

System/component degradation modeling is tightly connected with the usage, environmental and operational conditions, or, the corresponding load profile U composed of critical stress factors. It is recommended in practice to integrate the stress factor influence into the degradation modeling. However, studying the fault progression as a function of varied load profiles is beyond the scope of this paper. Thus, here, we fix the SMPS load profile including three stress factors: input voltage, load resistance and temperature. For the choice of modeling approach, we adopt the feature-based modeling, as the degradation of electronic components usually reflects in their performance parameters' drifting from the nominal values.

a) Aluminum Electrolytic Capacitor Degradation

Aluminum electrolytic capacitors are known for their comparatively low reliability, and due to their criticality in SMPS systems they are a good candidate to study their degradation modeling and its contribution to system's failure. The performance of those components depends on the anode metal oxide film. With the thickening of anodic metal oxide film, the equivalent series resistance (ESR) increases and its capacitance decreases, while hydrogen produced from the cathode reaction accelerates the evaporation of electrolyte, which causes aluminum electrolytic capacitors' degradation.

The equivalent circuit model of the aluminum electrolytic capacitor in this application is as shown in Figure 5. In Figure 5, C_7 and C_{11} represent capacity values; R_{39} and R_{43} represent ESR values.

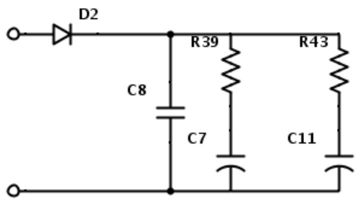


Figure 5. Aluminum electrolytic capacitor equivalent circuit model in PSpice.

Given a fixed operational temperature, the capacitor degradation rate is constant. The capacity and ESR values change as the aluminum electrolytic capacitor degrades, as expressed in Equations (1) and (2):

$$ESR(\mathrm{t}) = a_1 + \log(b_1 \cdot t + 1) \quad (1)$$

$$C(\mathrm{t}) = a_2 - b_2 \cdot t \quad (2)$$

where $a_1 = 0.3\ \Omega$, $a_2 = 220\ \mu\mathrm{F}$, $\mathrm{b}_1 = 7 \times 10^{-5}$, $\mathrm{b}_2 = 3 \times 10^{-5}$. The degradation model parameter values are empirically selected.

b) Feedback Resistor Degradation

In an SMPS system, the feedback circuit monitors the output voltage and compares it with a reference voltage. In the feedback loop, the degradation of feedback resistor plays a vital role in SMPS's reliability. Theoretically, with the reference voltage unchanged, an increase of feedback resistance will lead to a decrease of SMPS output current as indicated in Equation (3):

$$\mathrm{I} = I_N \times \frac{R_N}{R_a} \quad (3)$$

where $\mathrm{I_N}$ and $\mathrm{R_N}$ are SMPS average output current and feedback resistance under healthy condition, and R_a is the degraded feedback resistance. In this SMPS module, the feedback resistor is composed of two resistors in parallel. The empirical degradation models are as shown as follows:

$$R_{a1} = 3.9 + 7.8e^{-6} \cdot t$$

$$R_{a2} = 3.9 + 9.4e^{-6} \cdot t. \quad (4)$$

3. METHODOLOGY FOR MODEL-BASED DIAGNOSTICS AND PROGNOSTICS

In the field of PHM, fault diagnostics and failure prognostics techniques are usually classified according to the way that data is used to describe the behavior of the system: data-driven or model-based approaches. When the domain expertise is available to build a reliable degradation model of the monitored system, model-based diagnostics and prognostics approaches are preferable than the data-driven techniques. Figure 6 shows the systematic diagram for the proposed framework of model-based diagnostics and prognostics with Particle Filter (PF). In this case, the real-time data comes from the simulation model.

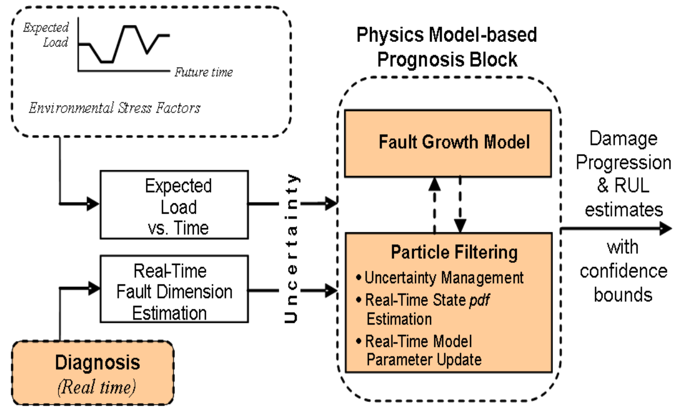


Figure 6. Model-based diagnostics and prognostics diagram.

3.1 Model-Based Diagnostics Module

A fault diagnostics module involves the tasks of fault detection and isolation, and identification (FDI). In general, this procedure may be interpreted as the fusion and utilization of the information present in a feature vector (measurements), with the objective of determining the operation states (i.e., being healthy or fault presence) of a system and the causes for deviations from particularly desired behavioral patterns.

In the model-based diagnostics framework, at any given instant of time, it provides a probability distribution function (PDF) estimate for meaningful physical variables in the system. In this case, simulation measurements at every time instant were collected from the integrated simulation model as introduced previously, and PDFs were generated from corresponding measurement histograms. Then, hypothesis testing through calculating current and baseline PDFs is used to generate fault alarms, and other statistical analysis tools may be used to extract additional information about the detection and diagnostic results. For example, in this case, POD is defined as below:

$$\text{POD} = 1 - \text{Type II error.}$$

Based on the calculated PODs from simulation, a fault detection threshold is set up in terms of POD. An illustrative example of fault detection confidence derived from type II statistical hypothesis testing with an example fault detection threshold is as shown in Figure 7. An illustration of fault progression with regard to the comparison of current and the baseline PDFs are as shown in Figure 8.

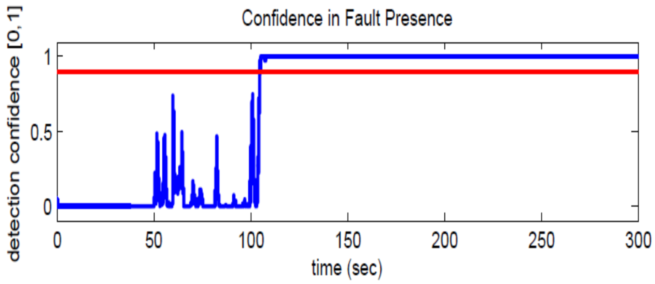
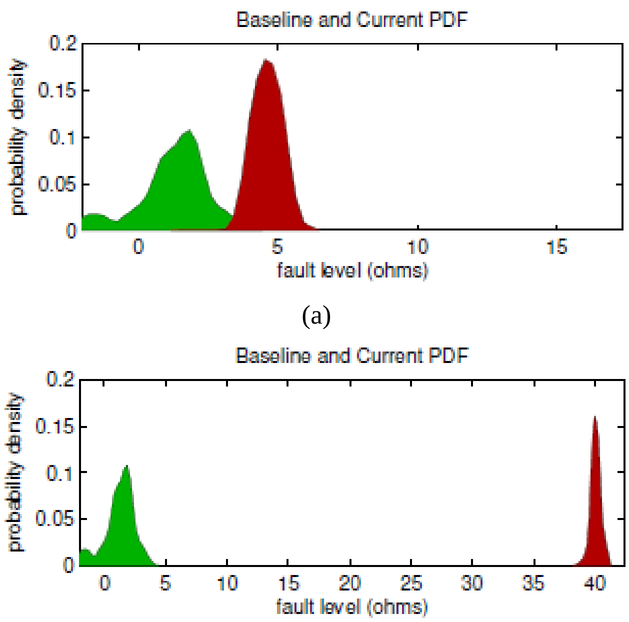


Figure 7. Estimator confidence metric derived from type II statistical hypothesis testing.



(a)

(b)

Figure 8. Baseline (left) and estimated (right) PDFs of (a) the mild and (b) the severe fault levels.

3.2 Model-Based Prognostics Module

A health-based failure prognostics module is usually triggered after the fault is detected, and the major task is to estimate RUL of the target system/component. In the process of model-based prognostics, the degradation model is expressed as a function of given load profile *U*, time *t*, and model parameters to be estimated Θ, or, mathematically,

$$\xi = \xi(\mathrm{t}, \theta, \mathrm{U}). \tag{5}$$

Note that Load profile *U* includes the contribution from the system external inputs and different stress factors as introduced before. The model parameters are estimated by integrating the degradation model with the observed health data. The RUL is calculated based on estimated model parameters.

In this paper, we realize the model-based prognostics in the PF framework. The methodology takes advantage of the empirical fault/degradation model, and a nonlinear process, a Bayesian estimation method using PF and real-time measurements. A merit of using PF for model-based prognostics is it combines RUL prediction and model estimation. Prognosis is achieved by performing two sequential steps, prediction and filtering. Prediction uses both the knowledge of the previous state estimate and the process model to generate the a priori state PDF estimate for the next time instant, or mathematically,

$$\mathrm{p}(x_t|y_{1:t}) = \int p(x_t|x_{t-1})\, p(x_{0:t-1}|x_{1:t-1})dx_{0:t-1}. \tag{6}$$

Unfortunately, this expression does not have an analytical solution in most cases. Instead, Sequential Monte Carlo (SMC) algorithms, or PF, are used to numerically solve this equation in real-time through the use of efficient sampling strategies. PF approximates the state pdf using samples or "particles" having associated discrete probability masses ("weights"), as expressed in Equation (7),

$$\mathrm{p}(\mathrm{x_t}|\mathrm{y_{1:t}}) \approx \widetilde{\mathrm{w_t}}(\mathrm{x^i_{0:t}}) \cdot \delta(\mathrm{x_{0:t}} - \mathrm{x^i_{0:t}})\mathrm{dx_{0:t-1}}, \tag{7}$$

where $\mathrm{x^i_{0:t}}$ is the state trajectory and $\mathrm{y_{1:t}}$ are the measurements up to time t. The simplest implementation of this algorithm, the Sequential Importance Re-sampling (SIR) particle filter, updates the weights using the likelihood of $\mathrm{y_t}$ as

$$w_t = w_{t-1} \cdot p(\mathrm{y_t}|\mathrm{x_t}). \tag{8}$$

Long-term predictions are used to estimate the probability of failure in a system given a hazard zone that is defined via a probability density function with lower and upper bounds for the domain of the random variable, denoted as H_{lb} and H_{ub}, respectively. The probability of failure at any future time instant is estimated by combining both the weights $w^{(i)}_{t+k}$ of predicted trajectories and specifications for the hazard zone through the application of the Law of Total Probabilities. The resulting RUL PDF, where t_{RUL} refers to RUL, provides the basis for the generation of confidence intervals and expectations for prognosis,

$$\hat{p}_{t_{RUL}} = \sum_{i=1}^{n} p(Failure|X = \hat{x}^{(i)}_{t_{RUL}}, H_{lb}, H_{ub}) \cdot \tag{9}$$

In this case, we use a predetermined failure threshold instead of a hazard zone for the illustration of methodology.

4. RESULTS

In the SMPS simulated degradation process, we fixed a load profile of temperature T = 25°C, input voltage V = 400V, load resistance Z = 220Ω, ran the integrated simulation model and monitored 10 output parameters: output current, voltage ripple, capacitance current ripple, capacitance voltage, transformer consumption, MOSFET consumption, MOSFET voltage, diode reverse voltage, and 47K resistance consumption.

4.1 Case Study: Aluminum Electrolyte Capacitor

4.1.1 Model-based Diagnostics

In the above-mentioned 10 output parameters, the amplitude of the output voltage ripple (VR) was substantially influenced by the degradation of aluminum electrolyte capacity. Therefore, VR amplitude was selected as a raw feature for further processing. In one cycle of SMPS degradation simulation, we collected 13 baseline and fault VR datasets with the time step of "thousand-hours", i.e., at $\mathrm{t = 0h, 1000h, \ldots, 12000h}$. At every time step, Gaussian noise $\omega_k \sim N(0{,}0.01)$ was added to every VR measurement to represent uncertainty introduced by measurement noise, and 60 measurements of VRs were collected with an example as shown in Figure 9. Based on the measurement, the histograms were computed and the histogram of every faulty dataset was compared to the one of the baseline dataset with an example as shown in Figure 10, and the PDF was computed from the corresponding histogram. Then POD was calculated and recorded as shown in Table 2. Note that, in this case, we fixed the false alarm rate (Type I error) at 5% and monitored POD change as fault evolves. Recall that POD = 1 – Type II error. Figure 10 and Table 2 both show that the POD values increased as the SMPS degraded over time. Here, we chose POD=95% as the SMPS fault detection threshold to trigger our prognosis module. As indicated in Table 2, based on the given fault detection threshold, the first 8 datasets (i.e., t=0h, 1000h, …, 7000h) was regarded as the training data sets, while the last 5 (i.e., t=8000h, …, 12,000h) as the testing datasets.

Table 2. POD between the faulty and the baseline datasets.

t (kh)	1	…	4	5	6	7	8	9	…	12
POD	0	…	0	0.018	0.334	0.769	0.994	1	…	1

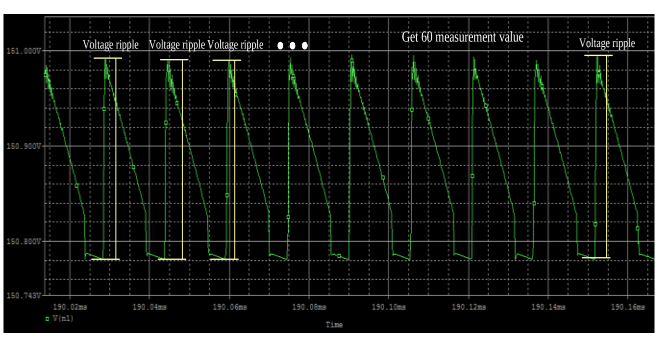


Figure 9. VR baseline (t=0h) measurements in PSpice.

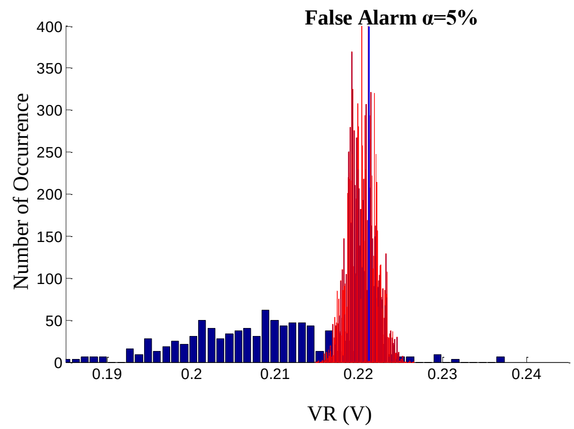


Figure 10. Comparison of faulty data at 6000h and baseline histograms.

4.1.2 Model-based Prognostics with Particle Filter

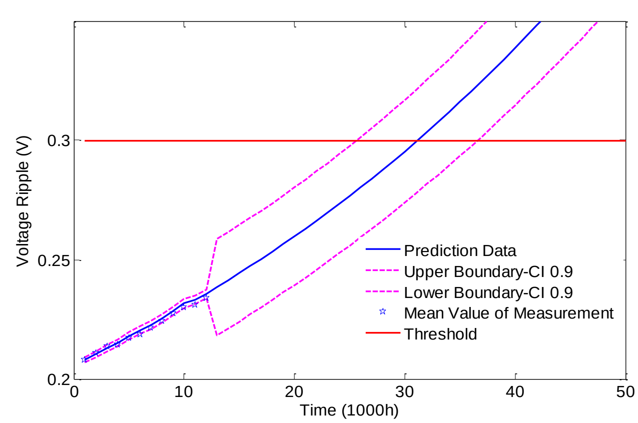
Once the fault detection threshold (i.e., POD = 95%) was reached, the SMPS RUL prognosis routine was triggered. An empirical degradation model is expressed by an exponential growth model as

$$\mathrm{x = a \cdot exp(bt) + c,} \tag{10}$$

where x is VR, t is time, and a, b, c are unknown model parameters. The above SMPS degradation model can be rewritten in an iterative form of

$$x_{t_k} = \exp(b\Delta t)\left(x_{t_{k-1}} - c\right) + c. \tag{11}$$

Both the model parameters and the RULs were estimated using PF. Here empirically we set the SMPS performance-based failure threshold as VR=0.3. The prediction diagram results in the form of probability are shown in Figure 11 (a). Figure 11 (b) and (c) show the RUL predictions at arbitrary cycles of 6,000h and 1,1000h respectively, in the form of distribution along with the 90% confidence interval (CI). As indicated in Figure 11 (b) and (c), the probabilistic RUL prediction was updated and the prediction accuracy improved over time.



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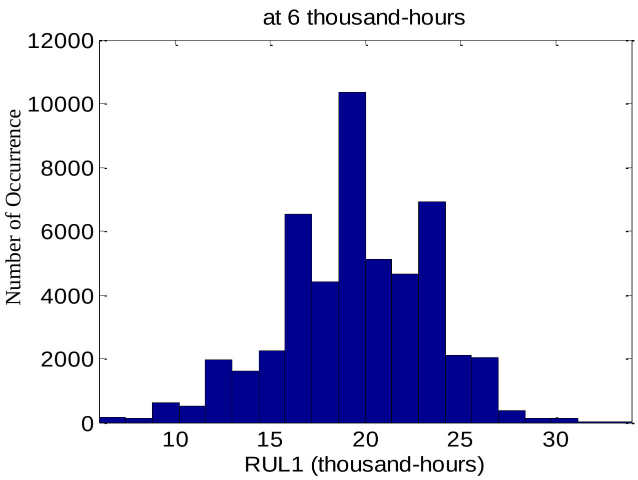

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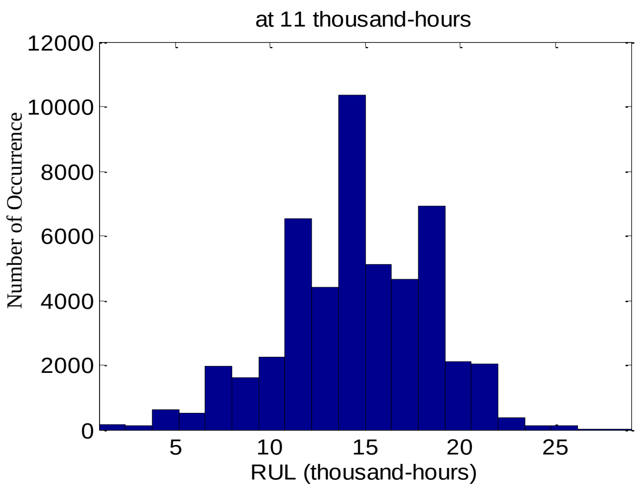
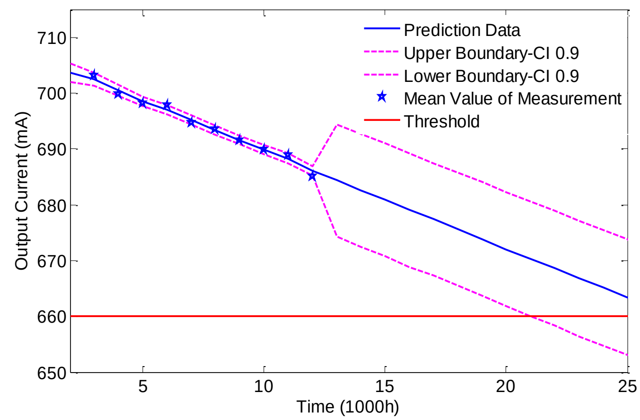


(c)

Figure 11. SMPS prognostics results in the case of aluminum electrolyte capacitor degradation: (a) prognosis module diagram results, (b) RUL pdf prediction at t=6,000 h, and (c) RUL pdf prediction at t=11,000 h.

4.2 Case Study: Feedback Resistor Degradation

The above-mentioned methodology is also adapted to the case of feedback resistor degradation diagnostics and failure prognostics. RUL results are illustrated in Figure 12. As indicated in Figure 12, the output current decreased as the feedback resistor degraded over time.



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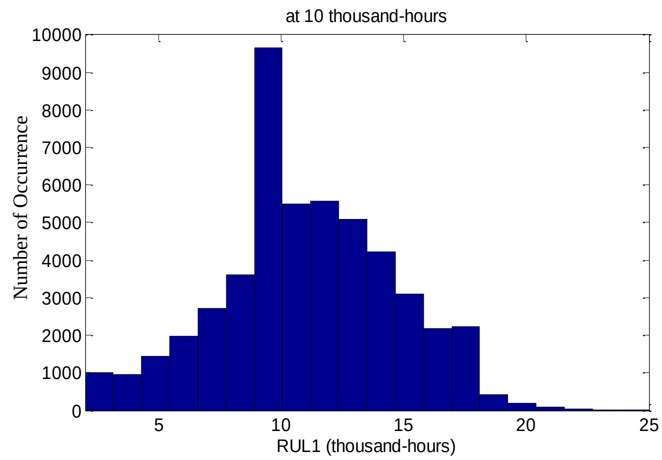

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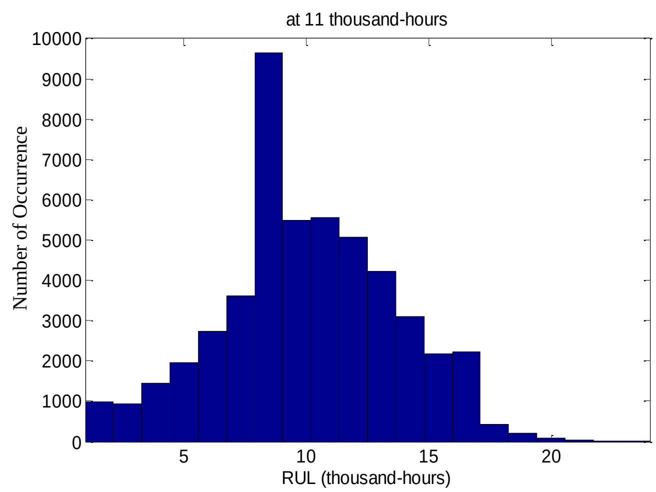

(c)

Figure 12. SMPS prognostics results in the case of feedback resistor degradation. (a) prognosis module diagram results, (b) RUL pdf prediction at t=10,000 h, and (c) RUL pdf prediction at t=11,000 h.

5. CONCLUSIONS

This paper introduces a novel framework of a model-based SMPS fault diagnostics and failure prognostics methodology, which leverages the knowledge of the component physics and degradation physics to assess the health status, diagnose faulty conditions and predict RULs. The methodology is based on electronic system simulation by employing a high-fidelity system simulation model and empirical critical component degradation models. General procedures and simulation results are presented in two case studies of critical component degradation. Although the discussion is limited in the scope of a specific simulated model from a commercially available SMPS product, the methodology can be extended to other SMPS systems with related adjustment of the simulation model and the component degradation models based on corresponding system test results and the knowledge of critical component ageing behaviors. Future work is needed to study other cases for single critical component degradation, to study the scenario when multiple faults are injected simultaneously (i.e., multiple component degradation), to study the impact of varied loads on the RUL predictions, and to explore the damage accumulation degradation modeling approach in addition to the feature-based modeling approach as adopted in this paper.

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